

INTELLIGENT MECHATRONIC SYSTEMS FOR ACCESSIBLE ROBOTICS: A REVIEW OF SIMULATION, SENSING AND HUMAN-MACHINE INTERACTION

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Abstract - The fields of robotics, education, assistive technology, smart environments, and human-machine interaction are rapidly recognizing the significance of intelligent mechatronic systems. These systems rely on a mix of manual input, software interfaces, simulation tools, cameras, and AI to function. An outline of recent developments in the field of accessible robotics and intelligent mechatronic systems is given in this lecture. Works produced mostly between 2022 and 2026 are the primary subject of the evaluation. The main areas of investigation are robotic simulation, trajectories, rerouting, safety monitoring, educational software, digital aids, and control based on EEG and brain activity. The studies we reviewed suggest that accessible robotics does not rely on a single technology. For users who have limited physical control, BCI technologies may be a great help. Natural interaction may be provided by systems that use vision and gestures. To ensure safe testing before to actual usage, simulation and route planning might be helpful. Robotic systems may be made simpler to develop using lightweight AI and learning from demonstration. Important for real-world use are, as the assessment reveals, trustworthiness, affordability, validation, and unambiguous feedback. This article lays forth a plan for future mechatronic systems that include intelligent, human-centered, and inexpensive technology.

Keywords: Intelligent mechatronics; human-machine interaction; Robot simulation; Gesture control; Vision systems; EEG-based Control; Artificial intelligence; Assistive technologies.

1. Introduction

The field of mechatronics and industrial robotics is undergoing fast development. Large corporations used robots mostly for welding, assembly, handling, and machining in the past. Robotic and mechatronic systems have many contemporary uses, including in the fields of education, smart homes, assistive technology, rehabilitation, and human-machine interaction. Tools for simulation, sensors, visual systems, and inexpensive computers all lend credence to this shift.

The use of AI to human assistance and treatment is a first promising avenue. Users may benefit from digital technologies via automated operations, easy feedback, and guided involvement. One technology-

enhanced therapeutic usage in this sector is a successful way for EMG-based (Electromyography) reprocessing therapy [1]. Recent studies have shown that healthcare and assistive technology settings greatly benefit from digital systems that are designed with humans in mind [2, 3]. These gadgets show what software, sensors, and human input are capable of, but they aren't really robots in the conventional industrial sense.

In this context, brain-computer interfaces are also quite important. They have the ability to translate human intent into instructions. Useful in situations when regular physical control is inadequate. As an example of communication assistance based on BCI, a brain-to-text word prediction system for English and Romanian was built [4]. Recent research has shown that brain-

computer interfaces (BCIs) based on electroencephalograms (EEGs) may aid in communication, rehabilitation, and smart control applications [5], [6].

BCI systems become even more relevant when they are connected with mechatronic devices. In this case, the user does not only send a message. The user can control a physical or digital action. A prosthetic lower limb controlled through EEG signals and implemented with Raspberry Pi 4 was proposed as a low-cost example of this idea [7]. Recent reviews on neurorehabilitation and prosthetic control also show that wearable and BCI-based systems can help users regain part of their interaction capacity [8], [9].

Additionally, bio-inspired design is associated with this path. Mechanical components, biological ideas, sensors, and control mechanisms all come together in bionic systems. The practical analysis of the mechanical reaction of such a system was shown in a research on the dynamic behavior of a bionic leg prosthesis [10]. Design, comfort, control, and user adaption must be examined jointly, according to recent research on wearable rehabilitative devices and human-centered assistive systems [9], [11].

Accessible mechatronics also has applications in smart homes. A combination of software, controls, and sensors allow them to facilitate human interaction with their surroundings. The use of brain signals for the management of basic home equipment was shown by a real-time home automation system that used BCI technology [12]. Other recent studies also suggest that IoT, edge computing, and AI-based processing may enable smart environments and more flexible digital control [13]. This is important, since a mobile robot or robotic arm is not necessarily accessible robotics. It may also mean user responsive intelligent mechatronic setup.

Vision systems are also vital for intelligent mechatronics. Inspection, tracking and control cameras are beneficial, cheap and easy to install. For example, a study based on YOLO-v8 which identified defects caused by different 3D printer settings [14] might be utilized to aid in the production quality evaluations in additive manufacturing using computer vision. Deep learning methods for visual defect detection and inspection [15] might improve the quality control in the industrial process via the artificial intelligence vision.

Education may also make advantage of the same digital logic. Student success depends on accessible resources, constructive criticism, and personalized classroom settings. Research on individualized software programs for education shown how these programs may aid students' educational endeavors [16]. New evaluations demonstrate that AI in the classroom may aid with decision-making, customisation, and prediction [17], [18]. Students and engineers, not just specialized experts, will need

to be able to comprehend, test, and operate robotic systems of the future, so this is pertinent to robotics education.

Digital infrastructure is also present in contemporary intelligent systems. Data has to be processed, secured, monitored and sent. An example of software development for secure and flexible digital communication is a multithreaded VPN application that is capable to monitor the traffic and to circumvent geoblocks [19]. Recent studies on AI enabled software security and edge computing shows that smart applications demand trustworthy data processing and more secure digital workflows [13], [20]. This is of high importance, because to the wide use of local networks, cloud services and remote access in current robotic and mechatronic systems.

The study of robot motion is an essential part of mechatronics. The movement of a robot should be safe, smooth and efficient. The notion of least action was used to provide an optimization method for reducing the trajectories of articulated manipulators [21]. Recent research [22], [23] have shown that optimization, smoothness and quality of the pathways remain important open topics in intelligent robotic and mechatronic system trajectory planning.

Also, basic input modalities are required for human-machine interaction. Many users find gestures to be second nature. They may make simpler controllers and keyboards unnecessary. Hand gestures and local computing may facilitate accessible digital engagement, as shown by an inclusive offline learning platform that integrates gesture detection and local AI models [24]. Vision and wearable sensors may be used for accessible human-machine interfaces, according to recent research on hand gesture detection and gesture-based control [25], [26].

Institutional and educational decision-making may also be aided by artificial intelligence. One way data-based models may help with academic administration is shown in a ML research that aimed to guide institutional choices and forecast student success [27]. Prediction tools may assist with early intervention and improved planning, according to recent research on learning analytics and AI in higher education [28], [29]. The educational setting is a crucial one for the testing, explanation, and transmission of new technologies, making this an important factor for mechatronics and robotics.

Data use, however, is more than just a technological issue. Another issue is the lack of trust. Users need openness, agency, and trust from institutions in order to consent to the use of their educational data for learning analytics, according to a GDPR-aware research [30]. Fairness and openness are crucial when using machine learning models for educational decision-support systems, according to

other recent research [31]. This issue also manifests in accessible robots. Before using the system in their everyday lives or in the lab, users need to trust it.

One further important aspect of contemporary robotics is simulation. This way, researchers may practice with a dummy robot before deploying the actual thing. Different levels of geometric continuities may affect velocity, acceleration, and motion quality, as shown in a research that examined the effects of C1, C2, and C3 on the trajectories of industrial robots [32]. Robot motion has to be evaluated thoroughly before physical usage, according to recent research on industrial robot positioning errors and trajectory planning [33], [34].

Robots that are accessible also rely on teleoperation. By using this technology, a person may indirectly or remotely operate a robot. A vision-based teleoperation system for an articulated robotic arm showed how hand tracking can be used for intuitive robot control [35]. Recent works on human-robot interaction and gesture-based teleoperation also show that camera-based systems can make robot control more natural and easier to understand [36], [37].

Another fundamental issue with robot simulation is path planning. The goal is for the robots to reach the destination while avoiding obstacles. To simulate this issue, a Python program called RoboDK was used to create a route planning algorithm that avoids obstacles. The program made use of a free-space graph and robot-level validation [38]. When testing the actual cell would be too difficult or costly, simulation-based approaches may be helpful, as shown in recent research on digital twins and robot route planning [39], [40].

Another approach is to learn by doing. This is an example of how a person may teach robot new skills by modelling them for it. A Python-based system for robotic item sorting was built in a virtual work cell using lightweight classifiers [41]. Recent research on robot learning via demonstration and imitation learning [42], [43] suggests that this strategy may reduce the load of programming and make robots more accessible to those without technical competence.

Robot planning also relies on accurate representations of workspaces. The planner's efficiency and productivity are affected by the layout of the workstation. A comparative analysis of Cartesian, cylindrical, and spherical grids in a graph-based obstacle-avoidance planner showed that different discretization strategies can lead to different planning results [44]. Recent research on sampling-based planning and grid-based planning also confirms that the structure of the search space can strongly affect robot motion planning [45], [46].

All accessible robots should include safety features. Even if a robot is intuitive, it still has to be safe for its human operator. The authors of the RoboDK robotic cell operator safety monitoring tool suggested a simulation-based approach that makes use of workspace masks and image processing [47]. New research on automated robot cell layout and human-robot cooperation further supports the idea that robotic applications need to take human presence and cell design into account directly [48], [49].

Finally, numerical techniques and model assessment are also necessary for intelligent mechatronic systems. Data could be missing values, skewed, or otherwise hard to work with. A comparison of regression models' extrapolation and interpolation strategies demonstrated how various numerical approaches might impact model performance [50]. Many mechatronic and robotic systems rely on data measured, predictions, corrections, and choices based on models, therefore this kind of study is helpful.

In light of these guidelines, this article examines accessible robotics via the lens of intelligent mechatronic systems. Topics covered in the paper include digital systems with an emphasis on the user, learning from demonstrations, vision-based teleoperation, trajectories planning, sensing, artificial intelligence-based processing, BCI control, gesture interaction, and safety monitoring. All of these subjects are considered together. In this sense human input, computer processing, mechatronic action and feedback are considered as interconnected links within a practical chain.

In this paper, the main contribution is a structured overview of the current research trends from 2022–2026. Topics covered by the research include accessible mechatronic platforms, digital infrastructure, local AI, vision-based interface, gesture recognition, BCI systems, and robot simulation and trajectory planning. This framework explains how to integrate smart, human-centric and cheap technology, which can be handy for future robotic systems.

2. Review Scope and Thematic Organization

The study's overarching goal is to survey ongoing efforts to improve intelligent mechatronic systems and make robots more accessible. A number of tools and experimental arrangements are highlighted. This work integrates several systems that rely on human input, such as sensors, AI, simulation, software tools, and more.

Mechanical parts are no longer limited to structures, motors, and controllers in today's mechatronic systems. Cameras, EEG sensors, local computers, ML models, robot simulation tools, and

user interfaces are all essential components of such systems. The combined efforts of these parts provide systems that are easier to test, change, and use in many settings.

The bulk of the works assessed were published in the period 2022-2026. Reasons for this time period include the popularity of low-cost hardware, vision-based control, BCI devices, local AI models, digital learning tools, robot simulation platforms and the ubiquity of digital learning. These responses may help industrial robotics, assistive technologies, school education and scientific investigation.

In order to organize the selected works, research directions were used. Because the studies that were considered did not all come from the same place, this strategy was used. Various articles investigate BCI systems. Some scholarly papers discuss the topic of robot route planning. Additional papers include software security, model evaluation, online instruction, teleoperation of robots, and gesture recognition. These papers cover a wide range of topics, but they all work towards the common goal of making intelligent and user-friendly mechatronic systems a reality.

Research in this field primarily aims to develop digital systems with the user and their assistive technology needs in mind. Experiments show potential benefits of software, sensors, and feedback on prosthetic devices, user engagement, therapy, and rehabilitation. With user experience and interactivity as the cornerstones of accessible robots, this is an essential stride forward.

The second method is based on EEG and BCI based control. As input data, these systems make use of brain impulses. A variety of digital instructions, including those for communication, home automation, and prosthesis control, may make use of the processed signal. Human purpose may be linked with software and mechatronic behavior in this approach.

The third way involves using visual and gestural cues to communicate. Cameras, hand tracking, gesture recognition, and image processing are all components of the systems in issue. They are useful because they allow for more natural management. Simple visual engagement, hand gestures, or body motions allow the user to send orders without the need for complex technology.

The fourth direction is robot simulation, route planning, trajectory planning and work space modeling. This is why these studies are so important – to test robot behaviour before it is really used. Reachability, motion quality, potential collisions, and route feasibility may all be checked with the use of simulation. Additionally, it enables the comparison of several varieties prior to using the actual robot.

The fifth way is to learn by doing with the help of lightweight AI models. Here, the user may show the

software what it needs to do a task, and the program can figure it out. Consequently, there could be a need for less manual coding. Engineers, students, and others without technical skills may find it easier to use robotic applications.

Operator safety and robotic cell monitoring are part of the sixth direction. People should think about safety while designing robots as they may operate in close proximity to humans. Visual aids, masks for the workplace, virtual cells, and safe-zone inspections may all aid in the early detection of potentially dangerous circumstances.

The last route consists of educational software, web-based systems, and numerical model evaluation. They aren't directly related to robotic arms, but they advance the same area of research. A foundation of intelligent mechatronic systems is data, secure communication, prediction models, user trust, and comprehensible software. These parts expand the range of uses for mechatronics and robotics in areas including research, education, and applied engineering.

The evaluation is based on a sensible logic of comparison. There are a number of questions that cover each set of works. Which input format is utilized? What does the final product look like? Who are the system's ideal users? What is the system's reproducibility level? Did you employ simulations, actual hardware, users, or datasets to evaluate the system?

The main emphasis of the present work is on input types such as electroencephalogram (EEG) signals, camera images, hand motions, data from robot simulations, user data and numerical data. The main outputs include digital commands, robot motions, categorization and prediction results, safety decisions and users' feedback.

Accessibility is one of the criteria for evaluation. The term "accessibility" in this context is defined as the ease of use of a system for users with varied physical control abilities, such as students, engineers, etc., with little or no training. Accessibility is possible via simple and low cost technology, intuitive user interfaces, natural input and local processing independent of sophisticated external infrastructure.

The effort and expense of implementation are also taken into consideration. Many robotic systems need advanced controllers, closed software or expensive sensors. Although these techniques may be quite successful, they may be hard to reproduce in smaller environments such as classrooms or laboratories. So, solutions built on popular cameras, Raspberry Pi boards, Python libraries, local artificial intelligence models, and simulation settings are the focus of the evaluation.

The review also makes use of validation. Verification of some works is done using physical prototypes. Simulations are used to test certain

works. Software experiments or datasets are used in some studies. Various validation types give varied degrees of evidence. Tests of the gear in practice show its efficacy. Simulation provides a means for testing and comparing at no risk. Datasets get you closer to testing algorithms.

The assessed research was not ranked in any quality order. They all serve different purposes thus it would be pointless to rank them. A BCI system is not up to standard vs a robot's route planner. A learning analytics tool is not the same as a vision-based safety system. The focus of the study is on the potential benefits and limitations of each path.

A shared system chain organizes the review. It all starts with input from either the user or their surroundings. Various forms of human input, such as brain signals, hand gestures, camera images, software actions, or measurable data, may be used as input. The input is read and processed by the system. Then a trajectory, prediction, command, or decision is generated. Finally, the mechatronic device, software tool or robot performs an action and delivers feedback.

The research directions of the study are linked up in this chain. BCIs are usually located at the place of entrance into the body. The sensing level is about the vision and gesture systems. Near the processing level, you'll find AI models. The level of motion planning is close to the robot's route planning and simulation components. The feedback and support level is close to the instructional software and safety tools.

The structure is used to further illustrate in more detail the main technology clusters. The objective is to show how these research fields might contribute to intelligent mechatronic systems of the future in accessible robotics.

3. Main Technology Groups in Intelligent Mechatronic Systems

According to the literature, there are a number of primary technological domains into which intelligent mechatronic systems fall. These sections are not entirely divided. Sensors, software, AI, simulation, and human input are often all used simultaneously by the same system. This section so introduces the main categories and describes their use in accessible robotics.

3.1 Human-Centered and Assistive Systems

The literature identifies many key technology areas that include intelligent mechatronic systems. These parts are not totally separate. Often they combine sensors, software, AI, simulation and human input all at the same time, in the same

system. Here, the key categories are introduced and their role in accessible robots is described.

One example of this kind of technique is the Eye Movement Desensitization and Reprocessing (EMDR) method of treatment. Technology is so evolved to the point that it can aid in guiding operations and controlling user interaction [1]. This system is not really a robot, but it's related to mechatronics since it relies on human input, timing, control and interaction.

Prosthetic and rehabilitation devices are also related to assistive systems. Bionic and wearable devices need mechanical design, sensor data, control logic and user adaption. The dynamic behavior of a bionic limb prosthesis is explored in [10] and explains how to analyze such a device from the mechanical and control point of view. Related study on wearable rehabilitative devices also indicates that design choices, comfort and user demands must be examined together [11].

This group is important since you can't build accessible robots just on technical performance. The system should also be easy to use. It must be clear to the user. It must offer comprehensible feedback. It also must be modified to meet the user's physical and cognitive constraints.

3.2 BCI and EEG-Based Control

Signals from the brain are used as input data by brain-computer interfaces. The fact that EEG data may be obtained using non-invasive equipment makes them a popular choice. The fundamental concept is to translate mental processes into spoken instructions or regulated behaviors.

Many potential applications of BCI systems are shown in the literature study. By making word predictions based on information linked to the brain, a brain-to-text system may facilitate communication [4]. In order to link EEG data with a mechatronic device, a prosthetic lower limb that is based on a BCI may be used [7]. Through the use of brain signals, a home automation system that is based on a BCI may manage basic smart home devices [12].

These systems are helpful as they provide an additional way to regulate the system. It is not always necessary for the user to use their hands or click a button. People who have trouble moving around may benefit from this. Additionally, it might be helpful for trying out different approaches to human-machine interaction.

Having said that, not every circumstance lends itself to the usage of BCI devices. Possible noise in EEG readings. When switching users, the signal might fluctuate. You may have to calibrate the system. It could take some practice for the user to figure out how to reliably issue commands. Because of this, BCI systems show promise, but they need undergo extensive testing before being used in everyday life.

3.3 Vision-Based and Gesture-Based Interaction

Vision-based interaction is one of the most practical directions for accessible robotics. Cameras are easy to use and are cheaper than many special sensors. A vision system can read hand movement, body position, objects, defects, or unsafe areas.

Gesture control is useful because it is natural for many users. The user moves the hand, and the system reads this movement as a command.

The inclusive offline learning platform with gesture recognition and local AI models shows how this idea can be used in an educational and accessible software environment [24]. Similar recent works also show that gestures can support wheelchair control and smart navigation [25], [26].

Systems may be useful even without direct control view. Computer vision may be used to discover problems caused by changed printing parameters, as proven in the study for 3D printing fault identification based on YOLO-v8 [14]. Moreover, deep learning has been shown to be successful in recognizing industrial flaws from images in prior study on surface defect detection [15].

Another area where vision based interaction might be useful to robots is teleoperation. With the use of hand tracking and video input, the user may control a robotic arm [35]. Recent studies have shown the potential of dynamic hand gestures for industrial engagement and robot teleoperation [36], [37].

The main advantage of this kind is simplicity of usage. Many experiments just need a camera and a computer model. The main limitations include lighting, background noise, camera position, hand occlusion and different users.

3.4 Robot Simulation and Motion Planning

Before using a real robot, it is common practice to evaluate its capabilities in a simulation. Due of the high cost of actual robots and the dangers posed by their clumsy motions, this is a practical solution. You may try out different pathways, barriers, reachability, robot movements, and workcell layout in the simulation.

Among the many subjects covered by this class is trajectory planning. It is important for a robot to be able to safely and efficiently travel from one location to another. One approach to shortening the trajectories of articulated manipulators is the optimization technique that follows the minimal action principle [21]. Trajectory planning is still a hot subject for smart mechatronic and robotic systems, according to another research [22], [23].

The quality of the motion is also important. Investigation of geometric continuities C1, C2 and C3 [32], show that geometric continuities may effect the robot speed, acceleration and smoothness of motion.

This is a crucial factor, since a route may be geometrically accurate, yet fail badly when applied to real robotic tasks.

Another important direction is the route planning with obstacles. A free-space graph-based route planning tool, RoboDK, depicts the process of building and validating a robot's path in a simulated environment [38]. The study on digital twins and virtual commissioning shows that simulation may be used to evaluate robots before real operation [39], [40].

Planning is another area affected by workspace modeling. A study that compares cylindrical, spherical and Cartesian grids [44] shows that the split of the workspace might influence the planning results. In other recent papers on RRT and RRT-based techniques [45], [46], the search strategy and the representation of the environment play an important role in route planning.

3.5 Learning from Demonstration and Lightweight AI

If the user is not interested in coding for the robot, learning via demonstration is an excellent option. The user merely has to show the work for the machine to learn. This will be useful for engineers, students and those who do not have knowledge in coding.

A Python-based robotic item sorting system [41] combines learning-by-demonstration with lightweight classifiers in a virtual workcell. This is valuable because it allows humans in the loop, data collection, model training, and robot behavior to be combined.

Lightweight models are needed since not every application needs a very huge AI model. Smaller classifiers are frequently easier to run, to test, and to explain. This is a life saver for laboratories and schools with limited hardware resources.

There has been recent research showing that this approach may lessen the need for manual programming work [42], [43] when it comes to learning via example and imitation. As the system does some of the legwork to translate the example into robot action, the user is free to concentrate on the job at hand.

Accessible robotics is strongly associated with this group. Robots that can learn from examples will have more potential users. This makes the robot more amenable to real-world applications and less reliant on expert programming.

3.6 Safety and Operator Monitoring

Any robotic device that comes into contact with humans must include safety features. While helpful and simple to use, a robot must also be able to prevent harm. Because people using accessible robotics do not necessarily have the necessary

training to operate the robots, this is of utmost importance.

One such answer is RoboDK's vision-based safety monitoring tool for robotic cells. It uses workspace masks and image processing [47] to monitor the position of the operator in a virtual robotic cell. In order to promote better workcell design, this sort of technique may aid in locating potentially dangerous places.

Safe interaction between human and robot is also a vital part of human-robot collaboration. According to new research on Industry 5.0, robots are starting to take over industrial jobs that are more geared toward humans [48]. Robotic cells are becoming more adaptable and versatile, as shown by automated robot cell setup [49].

Safety measures should be included at an early stage in the design process. It has to be built into the system from the get-go. Everything from the robot's route to its workspace to its sensors to its user interface to its feedback mechanism should be designed with safety in mind.

3.7 Educational Software, Data, and Digital Support

There must be software to back up intelligent mechatronic systems as well. Included in this category are resources for instruction, databases, encrypted messaging, prediction models, and assessment of these models. Although these areas don't seem to have anything to do with classical robotics, they really aid people in comprehending, testing, and utilizing technological systems.

Learners and adapters might find help in software programs. The research on individualized learning software demonstrates the usefulness of digital resources for students' learning [16]. Predicting student achievement and directing institutional planning are two other ways machine learning may assist with educational choices [27].

Another layer is added by learning analytics. It analyzes user behavior and provides decision-support based on collected data. Prediction tools may aid with early assistance and planning, according to studies on learning analytics and AI in education [28], [29]. Trust and data control are crucial when using user data, according to the GDPR-aware research [30]. Additionally, educational decision-support systems need openness and equity [31].

Also, the digital infrastructure is essential. Mechatronic and robotic systems may be Internet-connected, remote-accessed, connected to local servers or use cloud computing. VPN software provides one possible path ahead, at least for safe and flexible communication over the Internet [19]. Other study on edge computing and AI enabled

software security also indicate reliable data processing and safer digital workflows [13], [20].

An additional component of the broader support layer is numerical approaches. Extrapolation and interpolation techniques study suggests that data processing stages could alter model behavior [50]. This knowledge is relevant in the field since measured data, predicted values and corrected signals are typically employed in robotic control and decision making.

3.8 General View of the Technology Groups

The different subfields of technology presented here show that accessible robotics does not depend on one strategy. Using a BCI allows for the direct input of human intentions. Natural interaction is provided by systems that use vision and gestures. Robotests offer risk-free testing. Planning the route simplifies creating the motion. It's a lot easier to learn to code by watching a demonstration. The operator is protected by the safety equipment. There are mutual benefits for trust, data use, and instructional technology.

All of these paths, when combined, make up a smart mechatronic system. You get user feedback. This is input by the system, either via software or sensors. Data is processed by algorithms or AI models. It gives a safety recommendation, an instruction, a route, or a prediction. The mechatronic system / software tool / robot will then do something and provide the feedback.

This approach is important since it gathers various works under one roof. The studies reviewed differ, but they all have the common goal of making mechatronic and robotic systems more user-friendly, testable and suitable for human-centered applications.

4. Comparative Synthesis of the Reviewed Directions

The approaches outlined above illustrate that there are various practical aspects which may be utilized to compare intelligent mechatronic systems. Considerations include potential applicability to real-world systems, kind of input, user effort, software needs, amount of validation, and hardware cost.

When the user is unable to depend on typical physical control, technologies that are based on BCIs may be helpful. In addition to facilitating communication, they may also facilitate the control of smart homes and prosthetics [4, 7, 12]. One big advantage is the direct link you have to the user and the system. The main drawback is the signal stability. EEG data may be affected by background noise, user mental state, device location, and calibration.

It is often simpler to implement systems that rely on vision or gestures. The cameras and software models that they can employ are commonplace. Because of this, they may be put to good use in aiding control, educating, inspecting, and teleoperating [14], [24], [35]. They're good at relating to people naturally. Their major downside is how much the final result may be influenced by things like the lighting, the angle of the camera, the background and the user's movement.

Safe testing prior to actual usage is made possible by robot simulation and route design. Trajectories, obstructions, workspace constraints, and motion quality may all be checked by the user using these tools [21], [32], [38]. This is a beneficial choice for robots since completing testing on real equipment could be unsafe or expensive. One key caution is that the behavior of a simulated robot may not be the same as that of a real robot. Because of this, before putting the system into operation, it needs undergo simulation and then actual validation.

Less human intervention in robot programming is possible with demonstration learning. By just demonstrating the job, the user may teach the system new skills [41]. This will be useful for users with not much programming ability and for students and engineers. Learned behavior is very model and example quality dependent, which is the fundamental limitation.

Safety equipment is needed when robots are close to people. Potential dangers may be detected with the use of vision-based monitoring, masks for the workplace, and virtual cell inspections [47]. Future robotic systems should be designed around the user and the workcell, e.g. human-robot interaction, automated cell setup [48] [49]. Safety isn't the last thing to think about. It has to be a part of the design from the start.

Intelligent mechatronics may be used more widely with the use of data-based tools and educational software. With their help, users may learn, assess and understand technical systems [16], [27]. Educational AI and learning analytics may aid in planning and prediction but also trust of users and fair use of data is critical [28], [30], [31]. This is crucial because human acceptance is as important as technical performance in accessible robots.

But one thing all these routes have is offering unambiguous feedback. The user has to know what the system reads, how it decides, and what it does. This is important for tools for education, safety monitoring, robot simulation, BCI systems and gesture systems. Even a technically sound system may behave unreliably without specific input.

Another common theme is the need of balancing price with system quality. To help replicate the study, there are cheap cameras, Raspberry Pi boards, Python libraries, local AI models and simulation platforms. On the other hand, accuracy, speed, and

stability could all be worse with inexpensive systems. This is why the actual job has to be considered while choosing the system.

It is clear from the literature study that accessible robotics cannot be achieved with a single technology. When it comes to direct user intention, BCI systems are great. For organic communication, vision systems are a lifesaver. For risk-free testing, simulation is a lifesaver. AI models are good at two things: prediction and classification. Safety gear is priceless when it comes to safeguarding humans. Learning and adoption are supported by educational tools.

The future systems should integrate these technologies. To sense their environment, make decisions, test their products, and keep operators safe, robotic platforms may utilize vision, AI, simulation, and safety features. A user may engage via demonstration, software buttons, BCI, or hand gestures. This synergy has the potential to simplify and standardize robotic systems.

As a result, this study approaches accessible robotics as a multidisciplinary area. Hardware, software, input from humans, processing of data, and feedback are all part of it. Even the most robust systems aren't perfect. Their user-friendliness, safety, adaptability, and comprehension are further merits.

5. Current Limitations and Future Research Directions

The analyzed works show that the intelligent mechatronic systems evidently evolved. Still, there are some constraints. These restrictions include measurement, signal integrity, simulation accuracy, user trust, cost and assessment of practical application.

Brain-computer interface and electroencephalogram (EEG)-based systems have a main cap. These technologies are useful in communication, smart home management and prostheses control. On the other hand, EEG signals are not always steady. Noise, where the gadget is placed, how tired users are and the amount of training users have might affect them. This points to the need for more user testing and easier calibration for BCI devices.

The second constraint may be seen in systems that depend on vision or gestures. These systems are particularly practical in that they can utilize conventional cameras. But if the illumination is poor, the background is busy or the hand is partly covered, their performance could vary. Future systems should be better in real rooms, laboratories and industries.

There are limits to robot simulation. A correct virtual path may not always match the real robot behavior. This might happen due to the different

controller settings, calibration errors, speed constraints, excessive load, tool placement or even small differences between the real and virtual cells. Therefore, you should not consider simulation as a proof of final real performance, but rather as a preventive measure.

Lightweight artificial intelligence models and learning from demonstrations may simplify robots. Even still, these systems are model and example quality dependent. Bad modeling could lead to bad behavior when taught. Future work should include better training techniques, additional test cases and more user pleasant feedback.

Another hurdle is cost and reproducibility. Systems with cheap cost are suitable choices for education and micro-labs. For this, they may employ local AI models, Python tools, Raspberry Pi boards and cameras. However, cheap gear might lead to accuracy, speed and stability suffering. Further research should determine which jobs are feasible with less costly devices and which still need more durable gear.

Trust from users matters as well. It doesn't matter whether a system works properly if the user doesn't know how to use it. This applies to brain-computer interfaces, control systems, safety tools, educational software, and robot simulations. Future systems need improved input clarity, interaction security and decision transparency.

Validation is another outstanding problem. The simulation experiments are done on some of the works studied. Others utilize data sets or small prototypes. These tests are useful, but they can't necessarily demonstrate what the system would behave in the actual world. Longer testing sessions, more real-world settings, and more actual users should all be included of future studies.

It is equally important to keep safety in mind. Robots are becoming more human. They are used in industrial cells, smart settings, schools and laboratories. Future technologies will need to incorporate sensing, simulation, safe zones and transparent human involvement. Safety has to be an integral element of the design process, and not a concern after the system is constructed.

Combining many input modalities is a viable way for future deployment. System input techniques may include gestures, brain computer interface (BCI), software buttons, voice instructions, or watching a presentation. This might make the system more adaptive. The user has a backup input method if the first one doesn't function.

Another possible future direction is local and private AI. It's realistic to assume that certain systems will run independently of cloud storage. It helps to protect user data, assistive devices and education. "Local AI models could simplify the

system, improve data protection and reduce latency in smaller labs."

The four principles driving the intelligent mechatronic systems of the future are affordable, safe, readily tested and intelligible. Simulation, sensing, AI and human input should be used in balance. We shouldn't be for more precision alone. Enhanced usability, more accurate feedback, less dangerous control, and a better link to genuine user needs should also be priority.

6. Conclusions

This research addressed recent breakthroughs in accessible robotics and intelligent mechatronic systems. In the material we read, we see that controllers and mechanical parts are no longer the only building blocks of modern robotic systems. Hardware, software, cameras, AI, simulation tools and human input are employed too.

The study found BCI devices might assist those who struggle with conventional physical controls. You will be able to control your prosthesis, automate your home and interact with others using these technologies. Further testing under realistic conditions, easier calibration and better signal stability are still required.

Another interesting approach is systems depending on vision and gestures. Often the most user-friendly, they work with conventional cameras and the natural movements of the user's hand. Teleoperation, inspection, instruction, and assistive control are all areas that these technologies may help with. The primary constraints stem from factors such as illumination, camera placement, backdrop, and user mobility.

To the present, safe testing relies heavily on robot modeling, trajectory planning, and route planning. Researchers may use simulation to test the robot's movements before using the actual robot. Faster testing and less risk are two other benefits. Nevertheless, more validation is necessary before interpreting simulation findings as conclusive evidence of actual behavior.

Robotic systems may be made simpler to develop with the use of lightweight AI models and learning from demonstrations. These tactics may help students, engineers and customers who do not have much experience. This allows for less direct coding and makes more robotic applications available.

As proven in the review, all intelligent mechatronic systems need confidence, transparency and safe operation. From a strictly technical point of view, a system must work. It should also be user pleasant, secure and easily understood. This is what robot cells, smart settings, instructional tools and assistive systems all depend on.

In general, the field of accessible robotics should be seen as a multidisciplinary field. It involves

human input, data processing, simulation and feedback. The next generation of systems should have affordable hardware, local AI, vision-based sensing, secure robot modeling and intuitive user interfaces. This could open up the pathway for more user pleasant, flexible and practical mechatronic systems.

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